CLAIMS

We claim:

1. A method for enhancing an image containing endmembers, comprising:

   selecting at least one measure of disparity;

   partitioning at least one first set of said endmembers in said image into at least one second set of said endmembers, each said second set incorporating at least one site having some spectral content,

   wherein said at least one site is a generic element of a lattice, and

   wherein spatial consistency is imposed on said spectral content of each said site so that each said at least one second set is associated with a spatially smooth region in said image; and

   using said at least one measure of disparity, applying a linear mixing model to said at least one second set to globally label said at least one second set,

   wherein said method yields improvements in:

   assessment of the type and amount of materials in a scene;

   unsupervised clustering of a scene, and

   post-processing smoothing operations suitable for application to diverse techniques for terrain categorization and classification.

2. The method of claim 1 in which a multi-grid Gibbs-based algorithm is used to partition said at least one first set of said endmembers,

   wherein said algorithm is used to estimate an underlying and unobserved process, X^P, a discrete labeling Markov Random Field (MRF) process, that associates a label with each said site, and

   wherein said X^P is used to condition a spectral mixing process (SMP), and

   wherein said X^P identifies each said site that may be treated as homogeneous, and

   wherein said partitioning may proceed with multiple material types incorporated within each said site.

3. The method of claim 2 in which said partitioning using said multi-grid Gibbs-based algorithm proceeds in stages from coarse toward fine grid resolutions,

wherein the number of said stages is defined by the lattice structure of a neighborhood, ξ_s, forming a simple pattern such that a neighborhood of each said lattice element comprises near, intermediate, and far neighbors that are specific multiples of the grid resolution, σ, and

wherein the near neighbors are closest said lattice elements that may touch said site even if only at said site's corners, and

wherein the next 16 said lattice elements are intermediate neighbors, and

wherein the far neighbors are the 24 said lattice elements on the outside of said next 16 lattice elements, thus forming perimeter layers away from said site of interest at multiples of said σ, and

wherein use of said intermediate and far neighbors facilitates a faster global solution than using just said near neighbors, and

wherein use of said intermediate and far neighbors also enables said algorithm to remember label assignments from prior said stages, and

wherein said σ determines the spatial sampling of said algorithm at some specific said stage of multi-grid processing, such that at full resolution, i.e., σ = 1, said site corresponds to a single said lattice element, and

wherein all coarse resolutions involve neighborhoods of said lattice elements forming a square in which said σ is the number of pixels along one side of said square.

4. The method of claim 2 in which said Gibbs-based algorithm is initialized conventionally, wherein said initialization enables a post-processing smoothing algorithm that may operate on the output of at least one classification technique.

5. The method of claim 2 in which said partitioning is initialized randomly,

wherein said randomly initialized partitioning algorithm is best implemented as a multigrid process using an extended neighborhood system to attain reasonable global labeling accuracy,.

6. The method of claim 2 in which said partitioning is initialized using a pre-processing scheme.

7. The method of claim 6 in which said pre-processing scheme is a recognized classification technique.

8. The method of claim 7 in which said recognized classification technique is supervised.

9. The method of claim 7 in which said recognized classification technique is unsupervised.

10. The method of claim 2 in which said multi-grid Gibbs-based algorithm uses an energy function to model distinctions in said image,

wherein, using the Gibbs Equivalent Theorem with an appropriately defined graph, $\{S_P^{(\sigma)}, \xi^{P(\sigma)}\}$, said Gibbs-based algorithm may be derived, and

wherein a maximum *a posteriori* (MAP) estimate may be computed that maximizes $\Pr(X^P \mid g)$ by iteratively sampling from the local Gibbs distribution pertaining to each said site, $s \in S_P^{(\sigma)}$, and

wherein computational intensity is reduced and said global labeling is improved.

11. The method of claim 10 in which said MAP estimate of X^P, denoted as X_*^P, is calculated in a first step, termed the Expectation Step, by:

$$X_*^P = \arg\max \quad \Pr(X^P \mid X^\lambda) \qquad \text{and}$$

the maximum likelihood estimate (MLE) of a vector of proportions on a label lattice, β, denoted as $\hat{\beta}$, is calculated in a second step, termed the Maximization Step, by:

$$\hat{\beta} = \arg\max L(\beta \mid X^\lambda, X_*^P)$$

wherein said MAP estimate of X^P is used as if it were observed, and

wherein complex integration over all possible realizable partitions is avoided by said two-step process.

12. The method of claim 10 in which said MAP estimate is computed using ratios of the relationship: $\Pr(X_s^P = x_s^P \mid X_r^P = x_r^P, r \neq s) = \Pr(X_s^P = x_s^P \mid X_r^P = x_r^P, r \in \xi_s^{P(\sigma)}) = \frac{1}{Z_s} e^{-\frac{1}{T}U_s(x_s^P, g)}$

where: $Z_s = \sum_{x_s^P \in \Gamma} e^{-\frac{1}{T}U_s(x_s^P, g)}$ and

$U_s(x_s^P, g)$ = energy interaction of site $s \in S_P^{(\sigma)}$ with the neighborhood $\xi_s^{P(\sigma)}$

13. The method of claim 1 in which said at least one measure of disparity is selected from the group consisting essentially of: spectral angle, Euclidian distance, classical Kolmogorov-Smirnov measures, mean adjusted Kolmogorov-Smirnov measures, and combinations thereof,

wherein said image is defined with respect to a local neighborhood.

14. The method of claim 13 in which said local neighborhood comprises at least one non-traditional and locally-extended neighborhood.

15. The method of claim 1 in which parameters of said linear mixing model are estimated based on said endmembers in said at least one second set being associated with appropriate said sites therein to enable computation of an enhanced spectral mixing process (SMP),

wherein the set of material spectra, H, is represented as

$$H = \{h^{(1)}(\lambda), \ldots, h^{(N_{ends})}(\lambda), \lambda \in \Lambda\}$$

and $H_s \subset H$ is the set of material spectra at a pixel site s, N_{Ends} is the total number of said endmembers, and the spectra for the k^{th} said endmember is given by

$$h^{(k)} = (h^{(k)}(\lambda_l), \lambda_l \in \Lambda), \text{ if } h^{(k)} \in H_s.$$

16. The method of claim 1 further employing a simulated annealing method of partitioning hyperspectral imagery, said simulated annealing method initialized by a supervised

classification method to provide spatially smooth class labeling for terrain mapping applications.

17. The method of claim 1 providing an estimate of said model as a Gibbs distribution defined over a symmetric spatial neighborhood system that is based on an energy function characterizing spectral disparities in both Euclidean distance and spectral angle, wherein said energy function depends on distance measures termed disparity metrics that provide a measure of the dissimilarity between an individual said site, *s*, and said individual site's neighbor, *r*.

18. An efficient and accurate method for extracting features from hyperspectral data representing a scene by implementing a spectrally-optimal supervised classification algorithm that has been smoothed by a post-processing routine that imposes spectral/spatial constraints defined by the Gibbs prior probability distribution, $\Pr(X^P)$.

19. A method for extracting features from hyperspectral data representing a scene by initializing a partitioning algorithm with the results of a classifier to improve classification by providing initial estimates based on labels that, as applied under the proper conditions, are spectrally optimal, comprising:

a) performing a classification of the scene using a supervised classifier that selects the labeling $\hat{x}_s^P$ at each said site *s* that maximizes the probability $\Pr\left(X_s^\lambda \middle| X_s^P\right)$ of a process that is approximately of the form of

$$X_s^\lambda \middle| X_s^P = \arg\max N(\mu_{x_s^P}, \Sigma_{x_s^P})$$

where:

$\mu_{x_s^P}$ = the mean of the spectral vectors for the class label, x_s^P

$\Sigma_{x_s^P}$ = the covariance of said spectral vectors; and

b) initializing by the results in Step a), performing a spectral/spatial partitioning of said scene using the relationship:

$$\Pr(X_s^P = x_s^P \middle| X_r^P = x_r^P, r \neq s) = \Pr(X_s^P = x_s^P \middle| X_r^P = x_r^P, r \in \xi_s^{P(\sigma)}) = \frac{1}{Z_s} e^{-\frac{1}{T}U_s(x_s^P, g)}$$

where:

$$Z_s = \sum_{x_s^P \in \Gamma} e^{-\frac{1}{T} U_s(x_s^P, g)}$$

$U_s(x_s^P, g)$ = energy interaction of site $s \in S_P^{(\sigma)}$ with the neighborhood $\xi_s^{P(\sigma)}$.

20. A method employing a simulated annealing method of partitioning hyperspectral imagery for extracting features from hyperspectral data representing a scene, comprising:

using a Bayesian framework to develop a 2-step supervised Gibbs-based classification algorithm,

wherein said algorithm is capable of performing high quality spatially smooth labeling of said hyperspectral data; and

using a linear classifier to initialize said Gibbs-based partitioning algorithm,

wherein said initializing results in improved label accuracy and smoothness as compared to using only said linear classifier without said Gibbs-based partitioning algorithm, and wherein global labeling accuracy is increased as compared to a stand-alone randomly initialized said Gibbs-based partitioning algorithm, and

wherein said initializing said Gibbs-based partitioning algorithm with said linear classifier also reduces the computation by eliminating the need for a multi–grid process and by allowing said simulated annealing to start at a cooler temperature.